

Comparison of different lead–acid battery lifetime prediction models for use in simulation of stand-alone photovoltaic systems



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HIGHLIGHTS

- Lifetime estimation of lead–acid batteries is a complex task.
- This paper compares different models to predict battery lifetime in stand-alone systems.
- We compare a weighted Ah-throughput battery ageing model with other models.
- The battery charge controller significantly affects the lifetime of batteries.
- The results show the weighted Ah-throughput model provides more accurate values.

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ABSTRACT

Lifetime estimation of lead–acid batteries in stand-alone photovoltaic (PV) systems is a complex task because it depends on the operating conditions of the batteries. In many research simulations and optimisations, the estimation of battery lifetime is error-prone, thus producing values that differ substantially from the real ones. This error can indicate that the “optimal” system selected by the optimisation tool will not be optimal. In this paper, all of the components of a PV system have been considered simultaneously to simulate the behaviour of the system. One of these important components is the battery charge controller, which significantly affects the lifetime of batteries. The results of the simulations have allowed a comparison of the most common methods of battery lifetime prediction used by simulation and/or optimisation tools with a weighted Ah-throughput method developed a few years ago. The results show that this recent method provides more accurate lifetime values. In a simulation of a real off-grid household PV system where the real battery lifetime was 6.2 years, the weighted Ah-throughput model predicted a lifetime of 5.8 years; however, the other methods obtained lifetimes of more than 15 years. In a simulation of another PV system designed to supply the load of an alarm where the real batteries lifetime was 5.1 years, the weighted Ah-throughput model predicted a lifetime of 4.4 years; however, the other methods obtained lifetimes of more than nine years.

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1. Introduction

The ageing mechanisms of lead–acid batteries have been studied previously [1–5]. The most important ageing processes are anodic corrosion, positive active mass degradation and the loss of adherence to the grid, irreversible formation of lead sulphate in the active mass, short-circuit, loss of water and electrolyte stratification [3]. These processes are often inter-dependent.

Batteries subject to deep cycling regimes typically age by degradation of the structure of the positive active mass. The battery cycle lifetime shown in the datasheet of the batteries (usually 300–2000 full cycles depending on the technology) is obtained in laboratory tests under standard conditions. However, the real

conditions of the cycles in PV systems are habitually very different from standard conditions and the real cycle lifetime can be much lower.

Stationary batteries, which operate under float-charge conditions (in practice, float service may also include occasional partial discharges), typically age by corrosion of the positive grid. Under optimum float voltage conditions (i.e., without cycling), a theoretical maximum service life can be achieved, called floating lifetime. Its value is between 10 and 20 years depending on the technology (manufacturers usually show this value in datasheets). However, even in the batteries of UPS systems (operating at float service) the real conditions can be different from optimal, and the real floating life can be much lower than shown in the datasheet. Float life shown in the datasheet is usually reported at 20 or 25 °C, but the effect of temperature on float life is approximately a 50% reduction for every 8.3 °C increase in temperature [6].

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Battery lifetime prediction in stand-alone systems is a difficult task as it highly depends on the operating conditions. Many factors affect the life of the batteries, including the depth of the charge–discharge cycles, the current, the cell voltage, the performance of the charge controller (e.g., voltage and state of charge limits and regulation), the length of time that the batteries are in a low state of charge, the time since the last full charge, the temperature, etc.

Many studies have been published about the simulation and optimisation of renewable stand-alone systems including batteries. However, the battery lifetime has always been estimated in fixed values based on the experience of the researcher [7–16] or it has been estimated by calculating the number of equivalent full cycles [17–20]. In the best cases, it may be estimated using the cycle counting method [21–25]. Additionally, many simulation and optimisation software tools use these methodologies to estimate battery lifetimes [26–29]. However, the real lifetime of the batteries can differ from the estimated lifetime by many years using the mentioned methods, depending on the operating conditions. A high error in the estimation of the battery lifetime would imply a great error in the estimation of the total cost of the batteries in the net present cost (NPC) of the system; therefore, a real levelised cost of energy (LCE) may be very different from the expectation. This fact can imply that, when using optimisation tools, the selected design for the system can be very far from the optimal one.

2. Background and motivation

The thermodynamics and kinetics of the corrosion of lead in lead–acid batteries were first shown by Lander in [30]. Ruetschi studied the influence of crystal structure and inter-particle contact in lead–acid batteries [31] and reviewed the ageing mechanisms [3]. Failure mechanisms of lead–acid batteries were studied also in [32], and kinetic aspects of ageing factor were shown in [1]. Garche et al. [33] studied the influence of different operating conditions (e.g., cycling, self-discharge, and floating) on the lifetime of different lead–acid batteries for solar applications. Other researchers [34] showed that ageing mechanisms in valve-regulated lead–acid (VRLA) batteries also include negative-plate deterioration and poor separator-plate contact. More recent studies of ageing of VRLA batteries can be found in [35]. A classification of battery operating conditions in PV applications in four classes can be found in [36]. In another study, Svoboda et al. [37] classified lead–acid batteries into categories for lifetime considerations of the components of renewable systems and for analysing the properties and performance of these systems. Wenzl et al. [38] described a procedure for lifetime predictions including the relationships between stress factors and ageing processes. Cherif et al. [2] proposed a battery ageing model for stand-alone PV systems based on the initial model of Shepherd [39]. In 2008, Sauer and Wenzl [5] compared different approaches for lifetime prediction for lead–acid batteries. The models compared were (i) the physicochemical ageing model, which has high precision but also high complexity and high difficulty to obtain the parameters of the model and low calculation speed; (ii) the weighted Ah ageing model (the Schiffer model [4]), which has medium precisions, medium complexity and medium calculation speed; and (iii) the event-oriented ageing models that have low precision, low complexity and high calculation speed.

In 2007, Schiffer et al. [4] showed a comprehensive Weighted Ah ageing prediction model for ranking lead–acid batteries according to expected lifetime in renewable energy systems and autonomous power-supply systems. The cycles are weighted by factors that consider the operating conditions. The model was verified by comparing the simulation results with experimental test results. However, the experimental charge–discharge tests were

not the typical charge–discharge processes which occur in stand-alone PV systems. They used two profiles: “PV profile” and “Wind profile”. However, even in the “PV profile” the batteries were tested using very intense deep charge–discharge cycles, with charge currents of about I_5 (current that would fully charge the batteries in 5 h) and discharge currents of about I_{10} , performing three cycles per day, obtaining a lifetime of approximately 180 days for an OGi battery. The simulation results were verified with the tests, but the profiles used were not realistic (they were “accelerated” tests). In most real stand-alone PV systems, there is only one daily charge–discharge cycle and also the charge and discharge currents are much lower than those used in the tests. Realistic testing usually obtains battery lifetimes higher than four years, and in some cases, if the batteries perform low discharge cycles and are well-controlled by the charge controller, then their lifetime can be even higher than 15 years. Additionally, previous researchers did not model the PV output current nor did they account for the effect of the charge controller on the lifetime of the batteries, which is a very important issue as it prevents over-charge and over-discharge. Using a good charge controller (e.g., PWM with state-of-charge calculation algorithms) with appropriate settings for the battery technology, the same battery exposed to the same charge/discharge cycles can have a much higher lifetime than one using a bad charge controller with incorrect settings.

In this paper, we have modelled the whole integrated system (including PV, batteries, charge controller and inverter), taking into account the characteristics of the most common charge controllers. Additionally, we have compared four different models for the performance of the batteries (the model proposed in [4] and three others); and we have compared three models for the calculation of the lifetime of the batteries (the model proposed in [4], the equivalent full cycles counting model and the “rainflow” cycle counting model, which are widely used by engineers, technicians, and in software tools). We have simulated two realistic stand-alone PV systems and we have compared the real lifetime of the batteries with the lifetime predicted by the different models. We conclude that the Schiffer model shown in [4] is the only one that gives good results. The results show that, in many cases, the approximations of the equivalent full cycles or the rainflow cycle counting methods can be very inaccurate. In some cases, the expected lifetime is more than two or three times the real lifetime.

3. Mathematical modelling and simulation of the system

The stand-alone PV system model used in this work is described in this section. Fig. 1 shows the system, composed of the PV

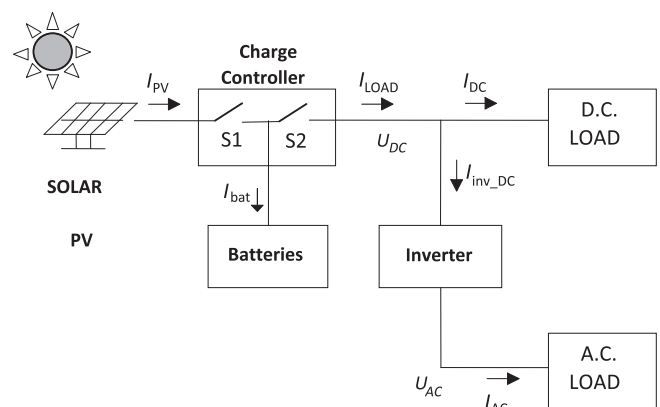


Fig. 1. PV system.

generator, charge controller, batteries and inverter. The load can be DC and/or AC.

3.1. PV generator

Calculating the hourly electricity generation of the PV generator requires knowledge of the hourly incident radiation in a typical year. In the cases where there is no irradiation hourly data available, we have used the average daily radiation on a horizontal surface for each month of the year as the solar input data. The data are converted into the average clearness index for each month using the Rietveld equation [40]. Then, the clearness index is obtained for each day of the year and the global hourly irradiation over the surface of the PV panels is calculated according to the Graham model [41]. The Graham method is suitable because it takes into account the uncertainty associated with the available irradiation data.

If no maximum power point tracking (MPPT) system is included in the PV system, the current supplied by the panels during hour t is calculated as follows (Fig. 2, left):

$$I_{PV}(t) = I_{SC} \cdot \frac{G(t)}{1 \text{ kW/m}^2} \quad (1)$$

where I_{SC} [A] is the shortcut current of the PV generator and $G(t)$ [kW/m²] is the average irradiance over the surface of the PV panels during hour t .

The PV cell temperature, T_c [°C], can be calculated using:

$$T_{(c)}(t) = T_{(a)}(t) + \left(\frac{NOCT - 20}{0.8} \right) \cdot G(t) \quad (2)$$

where T_a is the ambient temperature [°C] and $NOCT$ is the nominal operation cell temperature [°C] (typically 44–47 °C). For high cell temperatures ($T_c > 40$ °C) and medium–high values of irradiance ($G > 0.5$ kW/m²), (e.g., 75 °C curve on right graph of Fig. 2), the PV output current $I_{PV}(t)$ is lower than the value from Eq. (1), and it must be corrected as follows:

$$I_{PV}(t) = I_{SC} \cdot \frac{G(t)}{1 \text{ kW/m}^2} \cdot \left[1 + \frac{\alpha}{100} (T_c(t) - 25) \right] \quad (3)$$

where α is the temperature coefficient [%/°C] (typically in the range –0.43 to –0.47%/°C).

If the charge controller includes a MPPT system, the PV panels always work at the maximum power point of the $I = f(V)$ curve, so the output current of the PV generator is:

$$I_{PV}(t) = \frac{P_{STC}}{U_{PV}(T)} \cdot G(t) \cdot \left[1 + \frac{\alpha}{100} (T_c(t) - 25) \right] \quad (4)$$

where P_{STC} is the output power at standard test conditions [Watt-peak, Wp] and $U_{PV}(t)$ [V] is the output voltage of the PV generator. It is the voltage rather the drop of current that leads to the reduction of power output.

3.2. The battery

3.2.1. Battery current

Every hour, the battery current is calculated as:

$$\begin{aligned} I_{bat}(t) &= I_{LOAD}(t) - I_{PV}(t) = I_{inv,DC}(t) + I_{DC}(t) - I_{PV}(t) \\ &= \frac{I_{AC}(t) \cdot U_{AC} \cdot \cos \varphi}{U_{DC}(t) \cdot \eta_{inv}(I_{AC}(t))} + I_{DC}(t) - I_{PV}(t) \end{aligned} \quad (5)$$

where U_{AC} [V] is the AC voltage, $U_{DC}(t)$ [V] is the DC voltage (which varies with time, fixed by the batteries and the charge controller), $\cos \varphi$ is the power factor of the AC load, and η_{inv} is the inverter efficiency (which depends on the output current supplied by the inverter). $I_{bat} > 0$ means charge; $I_{bat} < 0$ means discharge.

3.2.2. Battery models for calculating the voltage and the state of charge

Four different models have been considered to calculate the voltage and the state of charge (SOC):

- The Ah model [42], also shown in [17].
- The KiBaM model [43].
- A simplified version of Copetti model [44,45] shown in [46].
- The Schiffer model [4].

Due to lack of space, we refer the reader to the references shown.

3.3. Charge controller

The battery current and voltage are controlled by the charge controller (preventing overcharge or over-discharge).

3.3.1. Preventing over-charge

3.3.1.1. The on/off charge controller. The on/off charge controller performance is shown in Fig. 3. During the charge process, when the terminal voltage of the battery cell raises to the upper threshold (“High Voltage Disconnect”, HVD setpoint), the charge current is turned off, disconnecting the battery from the PV generator (in

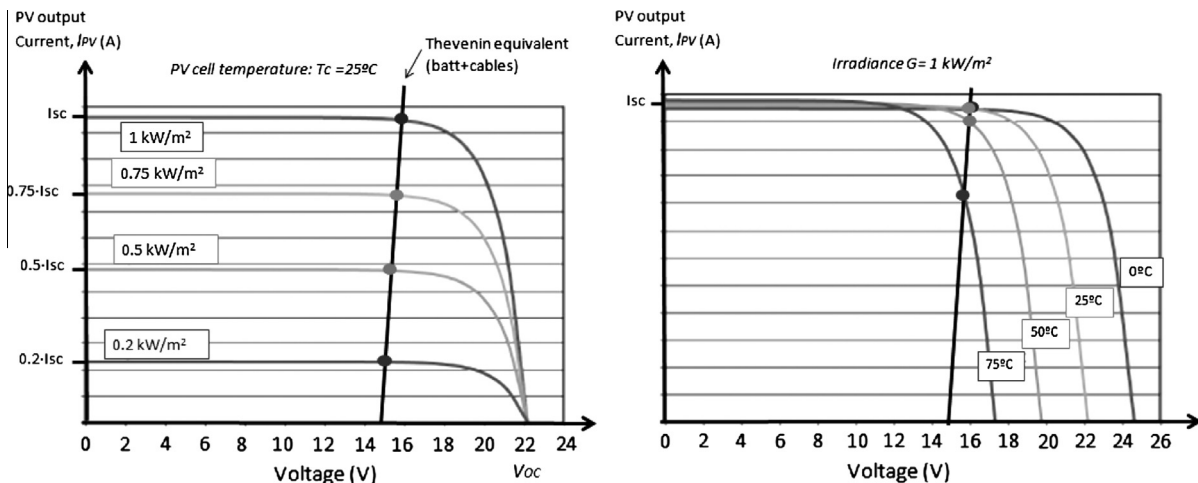


Fig. 2. Intersection of the $I = f(V)$ curve of the PV generator and Thévenin equivalent that it sees when the battery is fully charged. *Left:* Curves for a constant PV cell temperature ($T_c = 25$ °C) and irradiance G variable. *Right:* Curves for a constant $G = 1$ kW/m² and T_c variable.

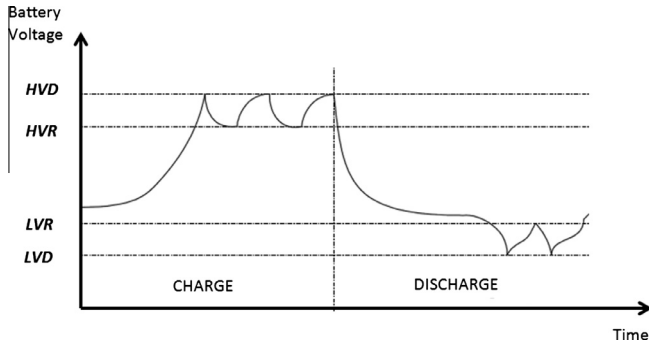


Fig. 3. Battery voltage vs. time during the charge and discharge processes controlled by an on/off charge controller.

Fig. 1, the switch S1 opens). When the voltage falls to the “High Voltage Reconnect” (HVR setpoint), the charge current is turned back on (in Fig. 1, the switch S1 closes).

3.3.1.2. The PWM charge controller. Many PWM chargers conduct charging in three stages: bulk, boost and float (Fig. 4). During the first stage (bulk), charging occurs at whatever current the PV generator is able to furnish. When the battery reaches the “Boost Voltage” (BV) setpoint, the current tapers to maintain voltage at the BV setpoint (boost stage). When the battery current drops to a certain level or a specific time has passed in the BV setpoint (BTime), the setpoint is dropped to a lower “Float Voltage” (FV Setpoint), permitting a small current into the battery, ensuring full charge while not causing excessive gassing.

PWM controllers intentionally overcharge the battery at regular intervals (*EInterval*, typically 30 days) or, applying a higher setpoint, called the “Equalisation Voltage” (EV setpoint), during a specified time (*ETime*), mixing the electrolyte (de-stratifying it) and ensuring that all of the cells within the battery are “equalised” at a full state of charge.

Some controllers use a high-performance algorithm with which the state of charge (SOC) can be calculated with a sufficient degree of accuracy and the battery can be optimally protected. This type of controller also applies SOC setpoints. The charge will include a boost charge stage if the battery has fallen since the last full charge to a SOC called “SOC for boost” (SOC_{boost}), otherwise the boost charge will not be used. If the battery has fallen since the last full charge to a SOC called “SOC for equalisation” (SOC_{equal}), the equalisation will be performed.

3.3.2. Preventing over-discharge

During the discharge process (Fig. 3), if the terminal voltage of the battery cell is discharged so deeply that its voltage reaches a

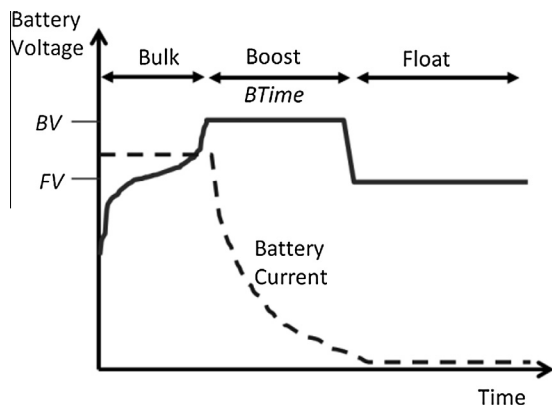


Fig. 4. Battery voltage and current vs. time during the charge process controlled by a PWM charge controller.

minimum threshold called “Low Voltage Disconnect” (LVD setpoint), the load is disconnected from the battery (in Fig. 1, the switch S2 opens). After recharging and reaching a “Low Voltage Reconnect” (LVR setpoint) the load is reconnected (in Fig. 1, the switch S2 closes).

As the voltage changes in relation to the charge and discharge currents and the state of charge, fixed LVD and LVR values are not optimal because, in the discharge process, the battery voltage depends on the current (high discharge currents imply low battery voltage). To solve this problem, many charge controllers use algorithms to calculate the SOC so the controller is able to disconnect the load at a specified “SOC to disconnect load” setpoint ($SOC_{disconnect_load}$) and it reconnects the load when the battery has reached a “SOC to reconnect load” setpoint ($SOC_{reconnect_load}$).

4. Battery ageing models

In this work, three different methods to estimate the lifetime of the batteries have been considered. They are explained next.

4.1. Equivalent full cycles to failure

This method is used by many simulation and optimisation tools [26]. It defines the end of the battery lifetime when a specified number of full charge–discharge cycles are reached. The IEC standard [47], replaced by [48] defines this number of cycles (Z_{IEC}).

The estimation of the lifetime consists of adding the charge (Ah throughput) cycled by the battery and calculating the number of full cycles (Z_N) as follows:

$$Z_N(t + \Delta t) = Z_N(t) + \frac{|I_{disch_bat}(t)| \cdot \Delta t}{C_N} \quad (6)$$

where $|I_{disch_bat}(t)|$ is the absolute value of the discharge current. When $Z_N(t) = Z_{IEC}$, the end of the lifetime of the battery is reached.

4.2. “Rainflow” cycles counting

This model is more complex and precise than the previous one. This is the method of cycles counting known as “rainflow”, based on Downing’s algorithm [49] that is used by HYBRID2 [50] and HOGA [26]. The method of cycles counting is based on counting the charge/discharge cycles Z_i corresponding to each range of the DOD (split in m intervals) for a year. For each interval there is a number of Cycles to Failure (CF_i) obtained from Fig. 5. Battery duration, in years, can be calculated as follows:

$$Life_{bat} = \frac{1}{\sum_{i=1}^m \frac{Z_i}{CF_i}} \quad (7)$$

4.3. The Schiffer weighted Ah-throughput model

The weighted Ah-throughput approach proposed by Schiffer et al. [4] is based on the assumption that operating conditions are typically more severe than those used in standard tests of cycling and float lifetime.

The actual Ah throughput is continuously multiplied by a weight factor that represents the actual operating conditions. The user can adapt the model to different battery types using the data sheet information on cycle lifetime and float lifetime.

The end of the battery lifetime is reached when its remaining capacity is 80% of the nominal capacity.

This model calculates the capacity loss by corrosion ($C_{corr}(t)$) and the capacity loss by degradation ($C_{deg}(t)$). The remaining battery capacity, $C_{remaining}(t)$ is the normalised initial battery capacity, $C_d(0)$, minus the capacity loss by corrosion and degradation:

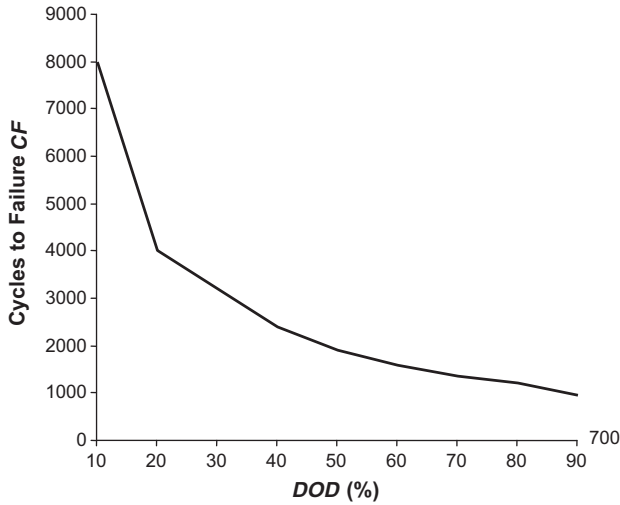


Fig. 5. Cycles to Failure vs. Depth of Discharge.

$$C_{\text{remaining}}(t) = C_d(0) - C_{\text{corr}}(t) - C_{\text{deg}}(t) \quad (8)$$

4.3.1. Degradation of active mass

The lifetime number of IEC cycles (Z_{IEC}) given in the battery datasheet is related to the stage at which the battery is 80% of its nominal capacity. However, as ageing is a combination of cycling and corrosion, the effective weighted number of cycles without corrosion would be higher, approximately $1.6 \cdot Z_{\text{IEC}}$ [4]. So the lifetime of the batteries would be reached when the weighted number of cycles without corrosion ($Z_W(t)$) is equal to $1.6 \cdot Z_{\text{IEC}}$. Then, the capacity loss by degradation (cycling) is calculated as:

$$C_{\text{deg}}(t) = C_{\text{deg,limit}} \cdot \exp \left[-C_z \cdot \left(1 - \frac{Z_W(t)}{1.6 \cdot Z_{\text{IEC}}} \right) \right] \quad (9)$$

where $C_{\text{deg,limit}}$ is the degradation limit (reached when the remaining battery capacity is 80% of the nominal capacity taking into account only cycling, not corrosion) and C_z is a constant equal to 5.

To calculate the capacity loss due to degradation, the Ah throughput is weighted with the impact of the SOC, the discharge current and the acid stratification. The weighted number of cycles without corrosion (Z_W) is calculated as:

$$Z_W(t + \Delta t) = Z_W(t) + \frac{|I_{\text{disch_bat}}(t)| \cdot f_{\text{SOC}}(t) \cdot f_{\text{acid}}(t) \cdot \Delta t}{C_N} \quad (10)$$

where f_{SOC} is a factor which takes into account the influence of the SOC and includes the impact of the current and f_{acid} takes into account the impact of the acid stratification.

4.3.1.1. Influence of the SOC. Low values of SOC over a long period of time imply loss of capacity due to mechanical stress on the active masses and also due to increasing size of the sulphate crystals. The magnitude of the lowest SOC since the last full charge and the length of time the battery remains at a low SOC both impact the battery lifetime. This impact on capacity loss is modelled by the SOC weighting factor (f_{SOC}), which is set to one at each full charge and increases with time since the last full charge, given by:

$$f_{\text{SOC}}(t) = 1 + (c_{\text{SOC},0} + c_{\text{SOC,min}} \cdot (1 - \text{SOC}_{\text{min}}(t))^{t_{\text{to}}}) \cdot f_i(I, n) \cdot (t - t_0) \quad (11)$$

where t_0 is the time of the last full charge, $\text{SOC}_{\text{min}}(t)$ is the minimum SOC since the last full charge, $c_{\text{SOC},0}$ is a constant which represent the increase in f_{SOC} with time at $\text{SOC} = 0$, $c_{\text{SOC,min}}$ is a constant to consider the impact of SOC_{min} and $f_i(I, n)$ is the current factor.

The impact of the current factor takes into account the effect on the lead sulphate crystals. This factor depends mainly on the current at the beginning of the discharge after a full charge (I). If the battery is charged to a SOC higher than 0.9 and lower than 1, this charge is considered a bad charge as the number of crystals decreases but their size increases. So the current factor is also affected by the number of bad charges (n).

The current factor can be calculated by the following expression:

$$f_i(I, n) = \sqrt{\frac{I_{10}}{I(t)}} \cdot \sqrt[3]{\exp\left(\frac{n(t)}{3.6}\right)} \quad (12)$$

where I_{10} is the 10 h current ($I_{10} = C_{10}/10$).

The number of bad charges is reset to zero when the SOC reaches 0.9999. When the maximum SOC reached during a charge (SOC_{max}) is between 0.9 and 1, n is increased as follows:

$$n(t + \Delta t) = n(t) + \Delta n = n(t) + \frac{0.0025 - (0.95 - \text{SOC}_{\text{max}})^2}{0.0025} \quad (13)$$

4.3.1.2. Influence of acid stratification. The influence of acid stratification on active mass degradation is taken into account by the factor f_{acid} . Low currents have higher impact on this factor as low currents are more inhomogeneous than high currents.

$$f_{\text{acid}}(t) = 1 + f_{\text{stratification}}(t) \cdot \sqrt{\frac{I_{10}}{|I_{\text{bat}}(t)|}} \quad (14)$$

where $f_{\text{stratification}}$ is the stratification factor, increased or decreased by the factors f_{plus} and f_{minus} .

$$f_{\text{stratification}}(t + \Delta t) = f_{\text{stratification}}(t) + (f_{\text{plus}}(t) - f_{\text{minus}}(t)) \Delta t \quad (15)$$

The lower the SOC since the last time acid stratification was removed (last full charge) and the higher the discharge current, the higher the increase in the stratification factor. The stratification factor decreases by diffusion and by gassing. The reader is referred to [4] for further details.

4.3.2. Corrosion

Corrosion mostly affects the positive electrode. The effects of corrosion on the negative electrode are neglected in this model. This model uses the concept of a corrosion 'layer' with lower conductivity, which grows during the lifetime of the battery. The effective corrosion layer thickness $\Delta W(t)$ is calculated in each simulation step depending on the corrosion voltage of the positive electrode, taking into account that corrosion processes vary according to potential of the positive electrode shown in [30,3]. The reader is referred to [4] for further details. The capacity loss by corrosion ($C_{\text{corr}}(t)$) is proportional to the effective layer thickness at time t , based on:

$$C_{\text{corr}}(t) = C_{\text{corr,limit}} \cdot \frac{\Delta W(t)}{\Delta W_{\text{limit}}} \quad (16)$$

where $C_{\text{corr,limit}}$ is the limit of the loss of capacity by corrosion and ΔW_{limit} is the corrosion layer thickness when the battery has reached the end of its float lifetime (given in the battery datasheet).

5. Results and discussion

We have considered two different stand-alone PV systems located near Huesca, in Spain: a household system and an alarm system. The first one is a typical low-consumption household where the batteries lifetime expected in the IEC conditions would be 15 or 20 years, but the real batteries lifetime is much lower due to the real operating conditions (charging and discharging currents

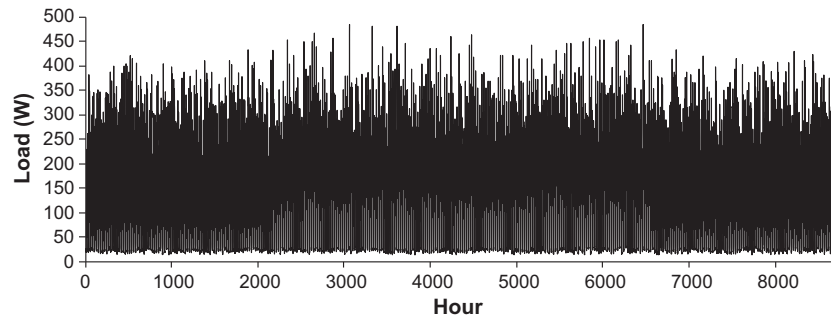


Fig. 6. Household load (one year).

are much lower than standard I_{10} and also, usually in winter, for weeks or even months, the batteries do not reach a fully charged state). The second one is a typical system where the batteries are

Table 1
Operational data of the systems.

	Household case	Alarm case
Nominal voltage DC/AC (V)	24/230	24/–
<i>PV generator:</i>		
– Number of PV panels in serial	2	2
– Number of PV panels in parallel	9	1
– PV panel power (Wp)	95	105
– PV panel nominal voltage (V)	12	12
– PV panel type	Polycrystalline	Polycrystalline
	Si	Si
– PV panel short current I_{sc} (A)	5.5	6.1
– PV panel open circuit voltage V_{oc} (V)	22	22
– PV panel $NOCT$ ($^{\circ}C$)	47	47
– PV panel α ($\%/^{\circ}C$)	–0.43	–0.43
– PV panel slope ($^{\circ}$)	60	55
– PV panel azimuth ($^{\circ}$)	0	0
<i>Battery bank:</i>		
– Number of batteries in serial	12	2
– Batteries nominal voltage (V)	2	12
– Battery type	OPZS	OGi
– Batteries nominal capacity $C_N = C_{10}$ (Ah)	546	54
– Batteries CF vs. DOD	Fig. 7	Fig. 7
– Batteries equivalent full cycles	1020	600
– Batteries float life at 20 $^{\circ}C$ (years)	15	10
Inverter-rated output (W)	500	–
<i>Charge controller:</i>		
– Type	PWM	PWM
– Rated current (A)	55	10
– Boost voltage BV (V/cell)	2.4	2.4
– $BTime$ (h)	2	2
– Float Voltage FV (V/cell)	2.3	2.3
– Equalization Voltage EV (V/cell)	2.45	2.45
– $EInterval$ (days)	30	30
– $ETime$ (h)	2	2
– SOC_{boost}	0.7	0.7
– SOC_{equal}	0.4	0.4
– LVD (V/cell)	1.85	1.85
– LVR (V/cell)	2.1	2.1
– $SOC_{disconnect_load}$	0.3	0.3
– $SOC_{reconnect_load}$	0.5	0.5
<i>Economical data for NPC calculation:</i>		
– Battery bank acquisition cost (€)	2592	170
– PV generator acquisition cost (€)	2880	360
– PV generator expected lifetime (yr)	25	25
– Inverter acquisition cost (€)	400	–
– Inverter expected lifetime (yr)	15	–
– Controller acquisition cost (€)	950	115
– Controller expected lifetime (yr)	15	15
– Total installation cost (€)	500	200
– Total annual O&M cost (€/yr)	100	40
– Lifetime of the system (yr)	25	25
– Average annual interest rate (%)	3	3
– Average inflation rate (%)	2	2

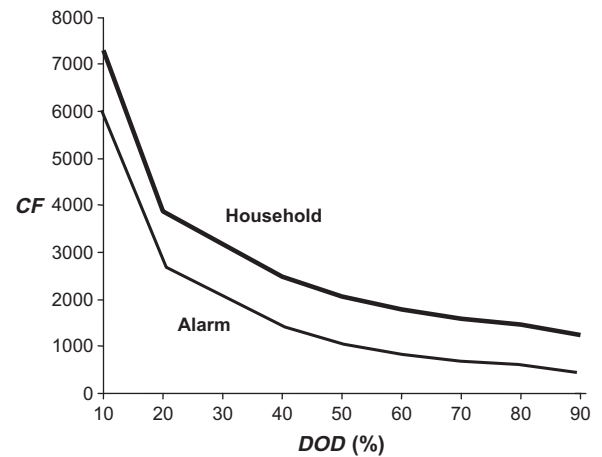


Fig. 7. Cycles to Failure vs. Depth of Discharge for the household and alarm systems.

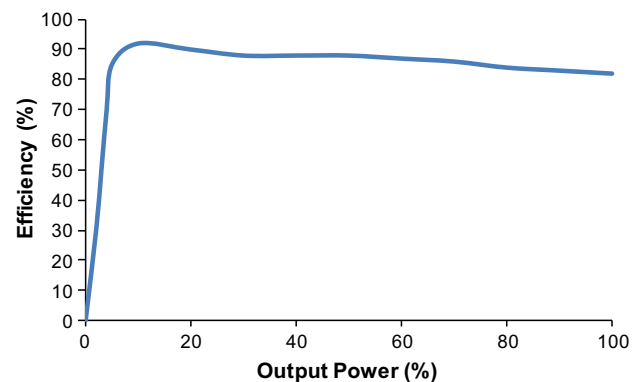


Fig. 8. Inverter efficiency (household system).

the most of the time at floating stage or near full charge, where, due to corrosion, the real batteries lifetime is much lower than float lifetime given in the battery datasheet.

5.1. The household system

The first case is an off-grid household. The system was designed to cover an average load of 2.8 kW h/day. However, the real average measured load was 3.7 kW h/day (AC for general purpose plus DC for lighting) from March to September, distributed as shown in Fig. 6. For the rest of the year an average of 3 kW h/day were measured (fridge load is much lower). On a few days in December and

Table 2
Average temperature and irradiation at the location of the systems.

	Household case		Alarm case	
	T_a (°C)	Average irradiation (kW h/m ² /day)	T_a (°C)	Average irradiation (kW h/m ² /day)
January	6.6	1.92	6.5	1.89
February	7.7	3.11	8.4	2.98
March	11	4.56	9.2	4.26
April	12.9	5.69	12.5	5.22
May	17.1	6.67	15.2	6.19
June	21.4	7.58	19.1	7.2
July	23.3	7.69	21.3	7.41
August	23.2	6.57	25.4	6.25
September	19.5	5.16	19.4	4.92
October	15.9	3.48	14.1	3.31
November	9.8	2.25	8.9	2.16
December	6.5	1.71	7.1	1.67

Table 3
Battery lifetime prediction (years) for the household case. Battery real lifetime: 6.2 years.

Prediction method	Batteries model			
	Schiffer et al. [4]	Ah	KiBaM	Copetti modified
Schiffer weighted Ah model	5.8	–	–	–
Average full equivalent cycles	19.1 [*]	18.9 [*]	18.8 [*]	19.8 [*]
Rainflow cycle counting	17.6 [*]	16.3 [*]	18.7 [*]	14.9

^{*} (>float life at 20 °C).

January, the users reported unmet load (the charge controller disconnected the load as the batteries were in the minimum SOC allowed). This unmet load was less than 0.5 kW h/year (0.04% of the total annual load).

The operational data of the system is shown in Table 1. The parameters for the Schiffer model were obtained by [51] and the corrosion speed curve vs. the potential of the positive electrode was obtained from [3]. The inverter efficiency is shown in Fig. 8. The average ambient temperature and irradiation are shown in Table 2.

The results are shown in Table 3. The real battery lifetime was 6.2 years, the Schiffer weighted Ah model [4] estimated 5.8 years, whereas the rest of the models estimated lifetimes higher than 14.9 years. Figs. 9–15 show the hourly simulation of the first six years using the Schiffer weighted Ah model. The loss of capacity is mainly by corrosion during the first years but during the end of the battery lifetime the loss by degradation is higher.

5.1.1. Effect on the minimum SOC allowed

We have evaluated the effect of changing the charge controller SOC setpoints for the disconnection and reconnection of the load.

The results are shown in Table 4. The NPC of the system and the LCE have been calculated considering the economical data shown in Table 1.

As the minimum-allowed SOC increases, the expected batteries lifetime also increases and, consequently, NPC and LCE decrease, obtaining a minimum LCE of 0.49 €/kW h (18% lower than LCE of the base case). However, high values for the minimum-allowed SOC would imply lower autonomy and that in the worst months (usually December and January) the load will not be fully covered and more unmet load events would be reported.

5.2. The alarm system

The second case is an off-grid alarm with a continuous DC load of 9 W (0.21 kW h/day). The parameters for the Schiffer model were obtained by [4] and the corrosion speed curve vs. the potential of the positive electrode was obtained from [3]. The operational data of the system is shown in Table 1 and the average ambient temperature and irradiation are shown in Table 2.

The results are shown in Table 5. The real battery lifetime was 5.1 years, the Schiffer weighted Ah model estimated 4.4 years, whereas the rest of the models estimated lifetimes higher than 9.1 years. Figs. 16–19 show the hourly simulation of the first five years using the Schiffer weighted Ah model. The graphs of the weighting factors are not shown as the batteries are mainly in float service and the weighting factors are near one most of the time (except for the last days when $C_{remaining}(t) < 1$ and factors and weighted number of cycles increase as shown in Fig. 18). The main cause of loss of capacity is corrosion.

5.2.1. Effect on the float voltage setpoint

We have evaluated the effect of changing the FV Setpoint of the battery charge controller. The results are shown in Table 6. In this system, the default FV Setpoint of the battery charge controller (2.3 V/cell) was not the optimal value (LCE is 1.28 €/kW h); this would have been 2.2 V/cell, with an LCE of 1.21 €/kW h (5% lower). The setpoints must be adequate for the battery and also for the application. In applications like this, where the battery spends most of its operating life at full or near full SOC, charge setpoints lower than in cycling applications are optimal.

6. Discussion

The two examples of PV systems shown are typical and they show that the “classical” models to predict the lifetimes of batteries (the equivalent full cycles counting model and the “rainflow” cycle counting model) do not work well in stand-alone PV systems. This is because in a PV system (without backup generator) the battery’s bank capacity is usually high (sized to cover between 3 and 8 days of autonomy), and the number of IEC cycles of typical batteries is also high (usually > 400 IEC cycles). Therefore, the total energy that can be cycled by the batteries in the standard IEC

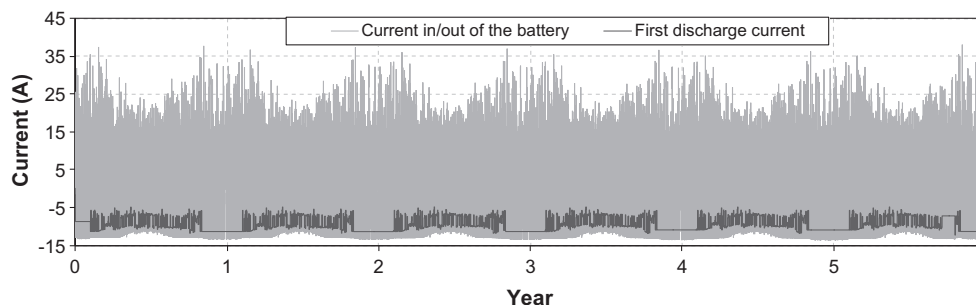


Fig. 9. Battery current for the household system.

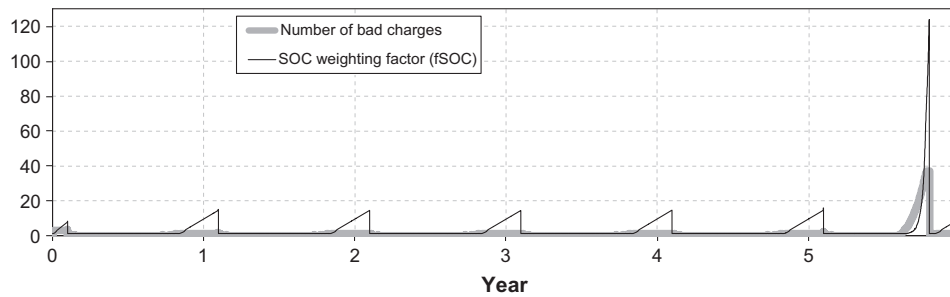


Fig. 10. SOC weighting factor and number of bad charges for the household system.

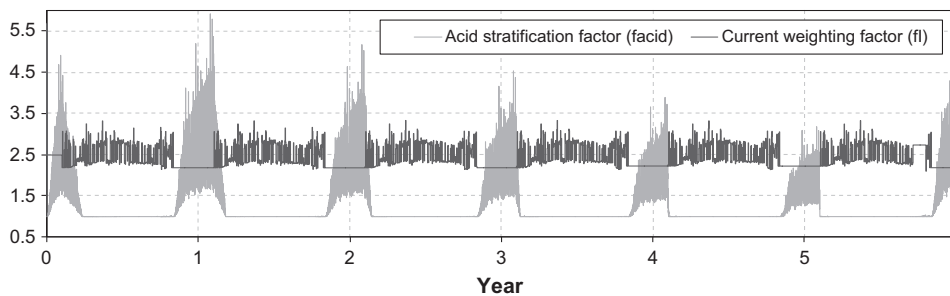


Fig. 11. Acid stratification factor and current weighting factor for the household system.

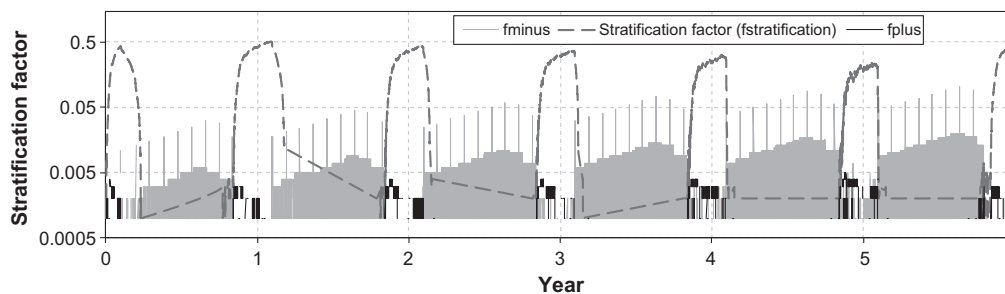


Fig. 12. Stratification factor and increasing and decreasing factors for the household system.

conditions is high; in many cases it is more than 15 or 20 times the real energy cycled in one year (i.e., the lifetime expected in the IEC conditions would be 15 or 20 years, which can be higher than the floating lifetime). The “classical” models assume that operating conditions are those used in standard IEC tests, which is why these models produce battery lifetime predictions that are very high. However, the real lifetimes are much lower in PV systems because the operating conditions are usually very different than those used in standard IEC tests: the charging and discharging currents are small compared to the standard I_{10} ; also, usually in winter, for weeks or even months, the batteries do not reach a fully charged state. In these cases, the Schiffer weighted Ah model is the only model that predicts battery lifetimes correctly.

However, in other kinds of systems, like hybrid PV-diesel systems, the battery-bank capacity is usually lower than in PV systems. These systems are usually sized to cover less than 3 days of autonomy, and the backup generator in the system keeps the batteries from remaining many days in low charge states. Their operating conditions are therefore not so different than those used in IEC tests, so the “classical” models in some of these cases can

predict the battery lifetimes almost as well as the Schiffer weighted Ah model.

Recommendations for achieving battery life extension:

- To improve battery lifetime, the value of the parameter $SOC_{disconnect_load}$ should be high (about 50% or higher).
- The battery charge controller must be correctly selected. Alternatively, if the controller's voltage and/or SOC limits are programmable, they must be adequate to the batteries and application.
- In systems in which SOC is always high and batteries are at a floating stage several hours a day (like alarm systems, Fig. 19), the float voltage should be lower than in applications where SOC is more variable. Also, the batteries should have high resistance against corrosion.
- In systems that experience periods of several weeks or even months in low SOC (like household systems, Fig. 15), the batteries should be able to withstand long periods in deeply discharged states. They should also be resistant against corrosion and against acid stratification.

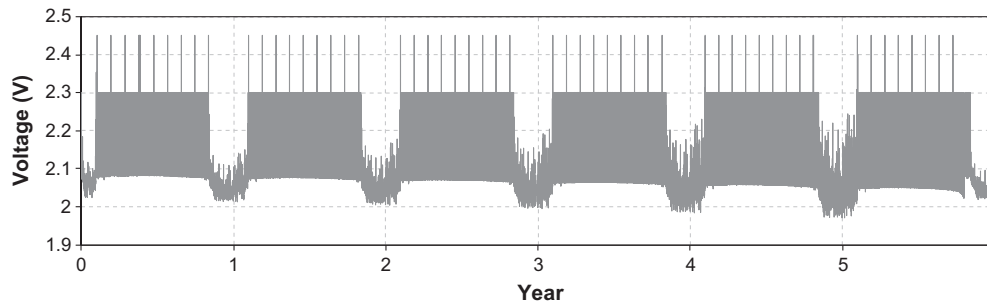


Fig. 13. Cell voltage for the household system.

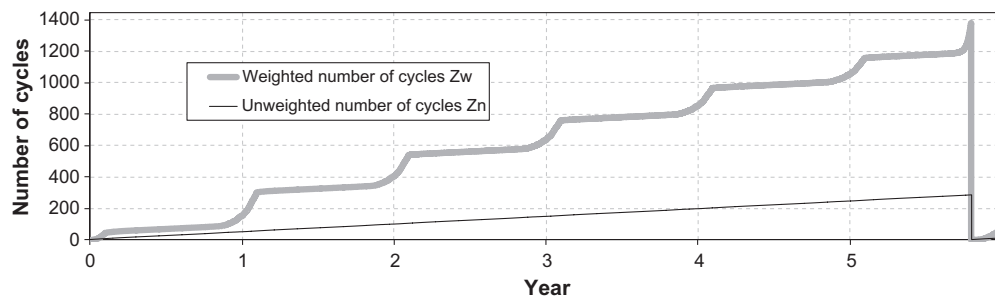


Fig. 14. Weighted and unweighted cycles for the household system.

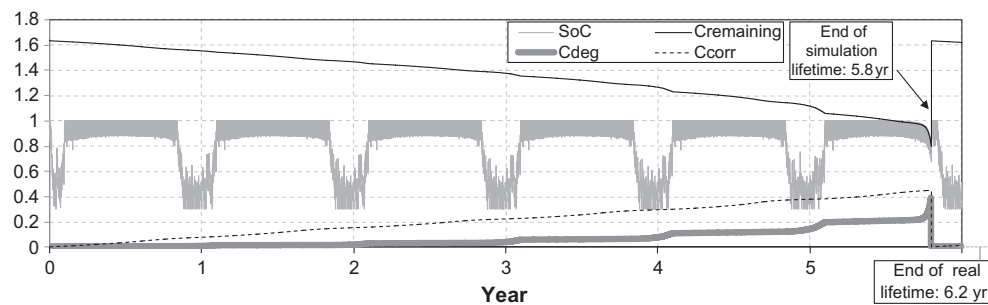


Fig. 15. SOC, remaining capacity, capacity loss by corrosion and capacity loss by degradation for the household system.

Table 4

Household case, Schiffer weighted Ah model, effect on the minimum SOC allowed.

$SOC_{disconnect_load}$	$SOC_{reconnect_load}$	Met/unmet load (%)	Energy autonomy (days)	Batteries expected lifetime (years)	Total NPC of the system (€)	LCE (€/kW h)
0.2	0.3	99.99/0.01	3.4	5.2 (−10.3%)	18750	0.61
0.3	0.5	99.96/0.04	3	5.8 (base case)	18624	0.60
0.4	0.5	99.93/0.07	2.5	6.3 (+8.6%)	16848	0.54
0.5	0.6	99.84/0.16	2.1	6.8 (+17.2%)	16100	0.52
0.6	0.65	99.75/0.25	1.7	7.5 (+29.3%)	15233	0.49

Table 5

Battery lifetime prediction (years) for the alarm case. Battery real lifetime: 5.1 years.

Prediction method	Batteries model			
	Schiffer et al. [4]	Ah	KiBaM	Copetti modified
Schiffer weighted Ah model	4.4	–	–	–
Average full equivalent cycles	16.1*	16.1*	16.1*	9.1
Rainflow cycle counting	16.1*	16.1*	16.1*	11.4*

* (>float life at 20 °C).

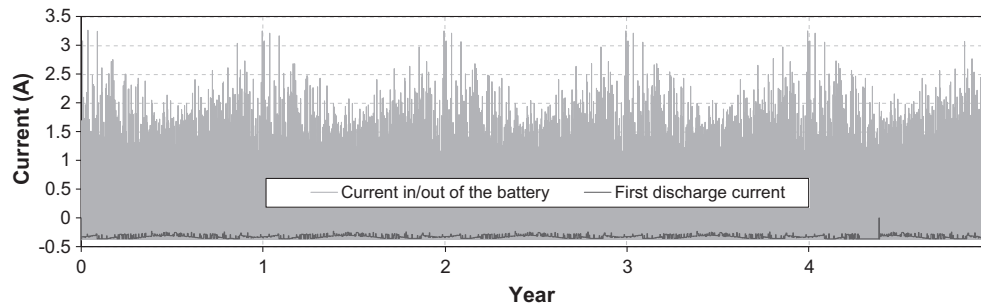


Fig. 16. Battery current for the alarm system.

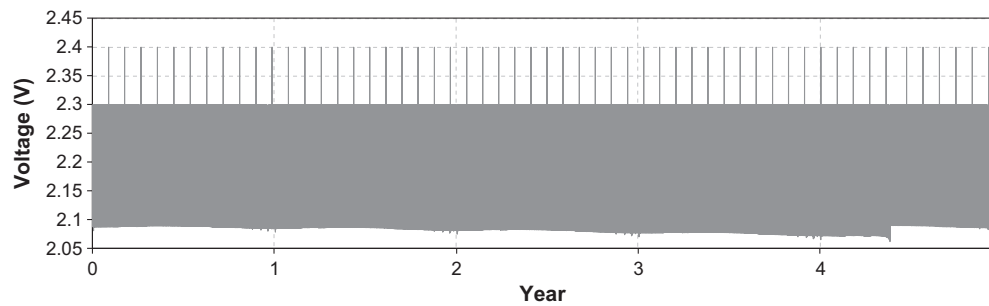


Fig. 17. Cell voltage for the alarm system.

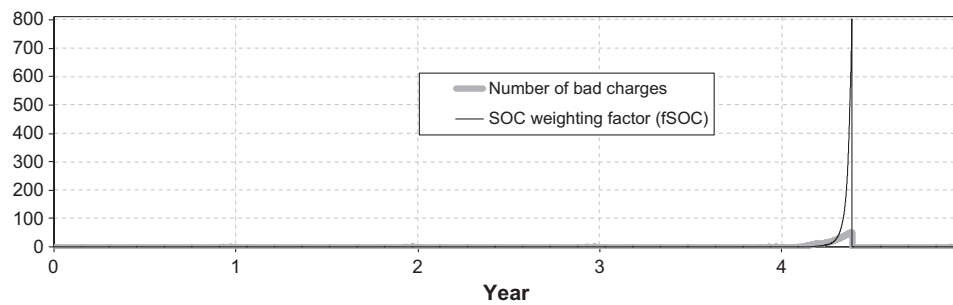


Fig. 18. Weighted and unweighted cycles for the alarm system.

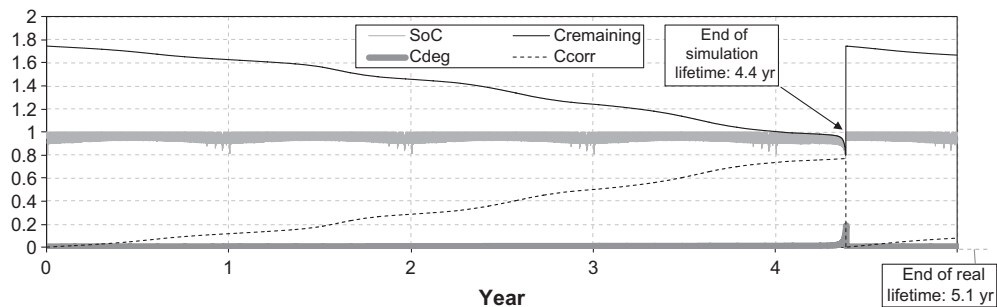


Fig. 19. SOC, remaining capacity, capacity loss by corrosion and capacity loss by degradation for the alarm system.

The effect on the SOC setpoints is notorious in batteries lifetime (and consequently in NPC and LCE) in systems where the batteries do not reach a fully charged state for long periods, like household system. The effect on the FV Setpoint is important in systems where batteries are the most of the time at floating stage or near

full charge, like alarm system. The LCE in the alarm system (>1.21 €/kW h) is much higher than in the household system (>0.49 €/kW h) because in the alarm system the PV generator and batteries were over-dimensioned to ensure the alarm works properly even during long cloudy periods and due to high specific cost

Table 6

Alarm case, Schiffer weighted Ah model, effect on the Float Voltage (FV) Setpoint.

FV Setpoint (V/cell)	Batteries expected lifetime (years)	Total NPC of the system (€)	LCE (€/kW h)
2.2	5.2 (+18.2%)	2338	1.21
2.25	4.8 (+9%)	2396	1.24
2.3	4.4 (base case)	2470	1.28
2.35	4 (–9.1%)	2558	1.33
2.4	3.8 (–13.6%)	2605	1.35

for very low power systems. The LCE of PV-batteries systems is high compared to grid-connected systems, but it is lower than LEC of stand-alone Diesel-batteries systems which is usually higher than 1 €/kW h but it can be much higher for very low power systems or for high values of fuel inflation.

7. Conclusions

Several battery performance and ageing models have been compared in the simulation of stand-alone PV systems. The ageing models generally used by researchers and simulation and optimisation tools (the equivalent full cycles model or the rainflow cycle counting model) do not correctly predict the ageing of the batteries; in many cases, the predicted battery lifetime is higher than the float life and two or three times higher than the lifetime obtained in real systems. However, using the Schiffer weighted Ah model [4], better results have been achieved, and predictions are very similar to real lifetimes, which are important in the technical and economical evaluation and therefore in the optimisation of these kinds of systems.

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